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Matt C. Howard

University of South Alabama, mhoward@southalabama.edu

Joseph F. Hair Jr.

University of South Alabama, JHair@SouthAlabama.edu

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*Mitchell College of Business, University of South Alabama, MHoward@SouthAlabama.edu*

Joseph F. Hair Jr.

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## Integrating the Expanded Task-technology Fit Theory and the Technology Acceptance Model: A Multi-wave Empirical Analysis

**Matt C. Howard**

**Joseph F. Hair Jr.**

Mitchell College of Business, University of South Alabama

*MHoward@SouthAlabama.edu*

### Abstract:

Task-technology fit theory proposes that the match between tasks and technologies, known as task-technology fit, has a positive relation with technology use and performance. Researchers have recently extended task-technology fit theory by conceptualizing task-technology misfit, which describes instances in which technology provides too few (too little) or too many (too much) features to perform a task. We link this newly expanded theory, which we label expanded task-technology fit (E-TTF) theory, with the technology acceptance model (TAM). We conducted a study and found that task-technology fit and too little significantly related to the variables in the TAM and that each ultimately had an indirect effect on use. In contrast, too much did not significantly relate to any variable in the TAM. These results support that E-TTF theory explains meaningful variance in the TAM, which suggests that integrating these theories is important for understanding technology use. Likewise, these results emphasize the importance of the multidimensional conceptualization that the E-TTF theory proposes. Too little (too few features) predicted outcomes beyond task-technology fit and meaningfully improved our model's predictive abilities. In contrast, too much's (too many features) relationships lacked significance, which emphasizes the need to distinguish types of task-technology misfit. Therefore, our study provides benefits for research on E-TTF theory, the TAM, and their integration.

**Keywords:** Task-technology Fit Theory, Expanded Task-technology Fit Theory, Technology Acceptance Model.

Gregory D. Moody was the accepting senior editor for this paper.

## 1 Introduction

Task-technology fit theory proposes that the match between tasks and technologies, known as task-technology fit, has a positive relation with technology use and performance (Dishaw & Strong, 1999; Goodhue & Thompson, 1995; Klopping & McKinney, 2004; Vanduhe et al., 2020). Howard and Rose (2019) recently extended this theory by identifying task-technology misfit, the extent to which technology does not match a task. These authors identified two constructs that represent task-technology misfit: 1) “too little”, which refers to conditions in which the applied technology provides too few features to perform the task, and 2) “too much”, which refers to conditions in which the applied technology provides too many features to perform the task. They also demonstrated that too little and too much differ from and have unique predictive abilities beyond task-technology fit. By identifying task-technology misfit (i.e., too little and too much), Howard and Rose (2019) have provided an avenue to further maximize technology use and performance because task-technology misfit captures variance in outcomes that task-technology fit does not. Such a discovery demands further investigation as it suggests that we can better predict important outcomes if we better understand misfit. To distinguish the expanded perspective from the original task-technology fit theory, we refer to the former as the expanded task-technology fit (E-TTF) theory.

The predominant focus on fit in extant research also indicates that we may have yet to discover theoretical nuances associated with task-technology misfit. Several authors following Howard and Rose (2019) have suggested outcomes that may relate to task-technology misfit (Howard & Gutworth, 2020; Hsiao, 2019; Li et al., 2019; Osang, 2019), which indicates that researchers have not yet or scarcely studied many relations. Likewise, while researchers have linked task-technology fit theory to other theoretical frameworks, they have yet to associate this recent extension to the theory (i.e., E-TTF theory) with such frameworks. These gaps in the present literature prevent researchers from completely understanding E-TTF theory. As task-technology misfit does not simply constitute the opposite of task-technology fit, one may predict many outcomes that the other may not. In these cases, outcomes that researchers have found not to relate to task-technology fit may still be associated with task-technology misfit. While only one possibility, it nevertheless shows that present unknowns likely hamper our theoretical and practical understanding of tasks, technologies, and their interface.

To address these concerns, we investigate the relationships that task-technology fit, too little, and too much have with another widespread theoretical framework: the technology acceptance model (TAM) (Bagozzi et al., 1992; Chau, 1996; Davis, 1985; Davis et al., 1989; Lee et al., 2003; Marangunić & Granić, 2015; Rafique et al., 2020). The TAM proposes a causal chain regarding how users perceive a technology that ultimately predicts whether they will actually use that technology (King & He, 2006; Pavlou, 2003). In this paper, we propose that task-technology fit, too little, and too much each predict the initial constructs in the TAM: perceived usefulness and perceived ease of use. We also propose that these initial relationships produce mediating effects such that task-technology fit, too little, and too much have indirect effects on attitude towards use, behavioral intention, and actual use via the prior linkages in the TAM. Figure 1 summarizes our proposed theoretical model. To test these assertions, we performed a four-wave time-separated study with a one-week separation between each wave.

With this study, we contribute to both research and practice. First, we replicate some initial findings regarding E-TTF theory that support the assertion that researchers should continue to apply the newly expanded theoretical approach. Second, integrating E-TTF theory with the TAM increases the former's scope by linking it with novel constructs associated with user adoption. Third, by connecting E-TTF theory to the TAM, we conceptually link E-TTF theory to all frameworks previously associated with the TAM. We provide initial support for these broader theoretical linkages, which enables future studies to confirm these associations. Fourth, our investigation increases the TAM's sophistication. Many authors have created revisions to the TAM that identify novel antecedents to the two initial constructs in the model. We follow that trend and propose that task-technology fit and task-technology misfit (i.e., too little and too much) are antecedents to the TAM. Lastly, we apply contemporary best-practices to perform a sophisticated statistical method, PLS-SEM, to simultaneously assess all relations in our model. As others have argued (Lee et al., 2003; Marangunić & Granić, 2015; Rafique et al., 2020), one can best assess the TAM via analyses that can simultaneously test all relationships, and future authors can mimic our analyses to perform their investigations.

## 2 Background

### 2.1 Task-technology Fit and Task-technology Misfit

Goodhue and Thompson (1995) created task-technology fit theory to understand the interaction of technologies and contexts (Goodhue, 1998; Maruping & Agarwal, 2004; McGill & Klobas, 2009; Zigurs & Buckland, 1998). The theory defines task-technology fit as “the degree to which a technology assists an individual in performing his or her portfolio of tasks” (Goodhue & Thompson, 1995, p. 216). As most scholars would agree, no one technology performs the best across all tasks and environments. Instead, task-technology fit theory recognizes that task efficacy differs depending on the context, and a technology may perform quite well in one circumstance but quite poorly in another. Given this observation, task-technology fit theory proposes that the interaction between tasks and technologies predicts task-technology fit and that task-technology fit mediates the effect that tasks’ and technologies’ interactions have on user reactions and performance. When investigating this theory, researchers typically measure how users perceive fit and study the outcomes of fit without directly assessing task or technology characteristics (Fuller & Dennis, 2009; Larsen et al., 2009; McGill & Klobas, 2009; Wu & Chen, 2017). The theory further suggests that use plays a role in this relationship, but researchers have often debated the topic (Gebauer et al., 2010; Larsen et al., 2009; Lin, 2012; Lin & Huang, 2008; Lu & Yang, 2014). Some researchers consider use to mediate the relationship that task-technology fit has with reactions and performance, whereas others consider use to moderate these relationships. Regardless, task-technology fit theory highlights the need to understand the interaction between tasks and technologies and the role that fit plays in predicting use, reactions, and performance.

Since its creation, task-technology fit theory has received support in hundreds—if not thousands—of studies, many of which have applied sophisticated methodological designs to robustly test the theory (Isaac et al., 2017; Khan et al., 2018; Sinha et al., 2019; Wu & Chen, 2017). Some studies have also begun to expand the theory’s boundaries, and it now has a much broader scope than its original conceptualization. As we mention above, Howard and Rose (2019) recently extended task-technology fit theory to incorporate two types of task-technology misfit, too little and too much. Howard and Rose (2019) defined task-technology misfit as “a mismatch between task and technology characteristics” (p. 3), too little as “when a technology does not include the desired features to perform a task (p. 4), and too much as “when an applied technology includes too many features to perform a task” (p. 4). They proposed these two types of task-technology misfit to negatively influence user reactions, use, and performance. Howard and Rose (2019) empirically demonstrated that too little influenced user reactions but not use or performance and that too much did not influence user reactions, use, or performance. They found that too little significantly related to both task-technology fit and too much, whereas too much did not significantly relate to task-technology fit. These findings support the assertion that task-technology fit, too little, and too much relate differently to the outcomes that task-technology fit theory specifies, which emphasizes the need to study the expanded perspective that E-TTF theory provides.

Howard and Rose (2019) and subsequent authors (Cagliano et al., 2019; Howard & Gutworth, 2020; Kabil, 2019) have called for future research to both replicate and extend prior findings regarding task-technology misfit—particularly by linking the concept with other established theories. We heed this call in this paper. To better understand task-technology misfit, we study E-TTF theory alongside the TAM. The TAM includes many key variables that needs to consider to understand user reactions and use—two of the same outcomes that E-TTF theory includes. Therefore, by integrating them, we can better understand E-TTF theory, the TAM, and the outcomes that both theoretical perspectives share.

### 2.2 Technology Acceptance Model

The TAM was created before task-technology fit theory, but the former remains one of the most commonly applied frameworks to understand whether users will adopt new technologies (Alkhowaiter, 2020; Dwivedi et al., 2020; Zhao et al., 2018). The TAM builds on the theory of planned behavior (Ajzen, 1985, 1991) and specifies a chain of user perceptions that ultimately lead to use (Bagozzi et al., 1992; Davis, 1985; Davis et al., 1989; King & He, 2006). To begin with, this theoretical chain proposes that perceived ease of use influences perceived usefulness and that both perceived usefulness and perceived ease of use predict attitudes toward a technology. Next, attitudes toward the technology predicts behavioral intentions to use the technology, but a prior construct in the causal chain, perceived usefulness, also predicts behavioral intentions. Lastly, behavioral intentions to use the technology predicts actual technological use. The TAM posits that each construct earlier in the chain indirectly influences the constructs later in the chain via the

intermediary constructs. Therefore, researchers should assess the model holistically rather than one linkage at a time as they may otherwise overlook the cumulative effects of each included construct. They can perform such a holistic assessment with PLS-SEM as we do in this paper.

Furthermore, the TAM was created to explain user adoption across most any scenario, and empirical research has largely supported this notion. Researchers have replicated the relationships that the TAM proposes—including the indirect effects—across many different technologies and contexts. As for technologies, researchers have found support for the TAM with wireless Internet (Lu et al., 2003), online classes (Roca et al., 2006), online banking (Pikkarainen et al., 2004), e-shopping (Ha & Stoel, 2009), telemedicine technologies (Hu et al., 1999), and many others. Regarding contexts, researchers have found support for the TAM with samples of students (Masrom, 2007), online shoppers (Koufaris, 2002), physicians (Hu et al., 1999), general employees (Chen et al., 2011), and many others. Therefore, the TAM represents an ideal theory to broadly understand whether users will adopt new technologies, and integrating it with other theories, such as E-TTF theory, may likewise enable researchers to more broadly apply these theories.

Also, researchers have created many newer TAM versions to provide better predictive abilities, particularly in specific contexts. These new versions include the TAM-2, TAM-3, unified theory of acceptance and use of technology (UTAUT), and the general extended technology acceptance model for e-learning (GETAMEL). These models include the original TAM as their core theoretical basis but supplement it with additional constructs (Abdullah & Ward, 2016; Scherer et al., 2019; Venkatesh, 2000; Venkatesh & Davis, 2000; Venkatesh et al., 2003). For example, the TAM-2 includes most of the original TAM as its central elements but includes additional constructs as antecedents to perceived usefulness (e.g., job relevance, output quality; Venkatesh, 2000; Venkatesh & Davis, 2000). Integrating E-TTF theory with the TAM also links it with these other theoretical frameworks as they have the same core theoretical basis. Therein, integrating E-TTF theory with the TAM has theoretical implications that go beyond an association with the TAM; rather, the implications may generalize to other TAM versions. That is, by integrating E-TTF theory with the TAM, one can then partially integrate E-TTF theory with the newer versions of the TAM (or, at least, their core elements), and future research can further investigate whether one can validly integrate E-TTF theory with these variations. For this reason, readers should not view our work here as an effort to integrate E-TTF theory only with the TAM but rather as an effort to integrate E-TTF with multiple theoretical perspectives.

### 2.3 Hypothesis Proposal

Given the above considerations, we formalize how we integrate E-TTF theory with the TAM in this section. E-TTF theory proposes that tasks and technologies interact to produce task-technology fit and task-technology misfit and that these constructs influence user reactions and performance. One can consider multiple variables in the TAM user reactions, but we suggest that task-technology fit and task-technology misfit (i.e., too little and too much) influence the initial constructs of the TAM's causal chain (i.e., perceived ease of use and perceived usefulness).

Prior research has supported that technology users can aptly perceiving the fit of tasks and technologies, and they are quick to make judgements of technologies based on their fit with tasks (Dishaw & Strong, Howard & Rose, 2019; Vanduhe et al., 2020). When a person uses a technology and identifies it as having beneficial features, they then begin to use these features more and develop more positive perceptions of usefulness and ease of use. Likewise, when a person uses a technology and perceives it as including too few or too many features, they may stop using these features and develop negative perceptions of usefulness and ease of use. When technologies match (or do not match) the task, we believe that users will be more likely to recognize such fit (or misfit) and perceive the technologies to be useful and easy to use (or useless and difficult to use). Likewise, when technologies do not match the task, we also believe that users will be more likely to recognize such misfit and perceive the technologies as useless and difficult to use.

Thereby, we predict that task-technology fit will have a positive effect on perceived ease of use and perceived usefulness but that too little and too much will have a negative on them. We note that the TAM suggests that any external variables influence the constructs in the model via indirect effects through these two initial antecedent constructs (Davis, 1985), and our proposed relationships align with both E-TTF theory and the TAM. Likewise, some authors have provided initial support for these proposed relations regarding task-technology fit and the TAM (Wu & Chen, 2017). However, we need further replications and no author has studied the relation between task-technology misfit and the TAM. Therefore, we do not know whether also accounting for the influence of too little and too much will replicate such effects.

- H1:** Task-technology fit positively relates to a) perceived usefulness and b) perceived ease of use.
- H2:** Too little negatively relates to a) perceived usefulness and b) perceived ease of use.
- H3:** Too much negatively relates to a) perceived usefulness and b) perceived ease of use.

As we mention in Section 2.2, one should study the TAM model holistically rather than one linkage at a time. For this reason, we study the relationship that task-technology fit and task-technology misfit have with the entire TAM beyond its first two constructs. Specifically, we propose that task-technology fit and task-technology misfit both produce indirect effects on attitude towards use via the mediators perceived usefulness and ease of use (Dwivedi et al., 2017; Patil et al., 2020; Rana et al., 2017), which results in a dual mediation effect.

People's interactions with technologies influence their specific perceptions regarding the technologies, and they build their general attitudes towards technologies from their more specific perceptions. For instance, a person may use a technology and perceive it as slow and cumbersome, which would then cause them to develop overall negative attitudes towards the technology. The same may be true for the dynamics that we study in this paper. When a person uses a technology and perceives either fit or misfit, these perceptions are believed to influence perceptions of usefulness and ease of use. In turn, these specific perceptions may develop into overall attitudes towards use regarding the technology. That is, a user may perceive a well-fitting technology as useful and easy to use, whereas they may perceive a poor-fitting technology as useless and difficult to use. In the former instance, the user would gradually develop positive attitudes regarding the technology, and, in the latter instance, the user would gradually develop negative attitudes regarding the technology.

- H4:** A) task-technology fit, b) too little, and c) too much have indirect effects on attitude towards use via perceived usefulness and perceived ease of use.

Next, we predict that task-technology fit and task-technology misfit have indirect effects on behavioral intentions towards use. This causal chain begins with task-technology fit and task-technology misfit, which influence perceived usefulness and perceived ease of use, which influence attitudes towards use, which influence behavioral intentions (Rana et al., 2016; Tamilmani et al., 2020). These proposed pathways result in a dual and sequential mediation effect.

While external influences certainly play a role, people develop their behavioral intentions to use technologies from their perceptions of and attitudes toward that technology. People tend to use technologies that they perceive favorably, and they tend to not use technologies that they perceive poorly. Because a technology's fit and misfit influence specific perceptions regarding the technology and these specific perceptions impact overall attitudes towards the technology, this causal chain continues such that the overall attitudes subsequently influence a person's decision to use or not use the technology. Through this entire chain, we believe that task-technology fit will ultimately cause users to have greater intent to use a technology, whereas task-technology misfit will ultimately cause users to have less intent to use a technology.

- H5:** A) Task-technology fit, b) too little, and c) too much each have indirect effects on behavioral intentions via perceived usefulness, perceived ease of use, and attitude towards use.

Lastly, we predict that task-technology fit and task-technology misfit have indirect effects on use via the same causal chain as above, but behavioral intentions subsequently influence use, which produces a dual and sequential mediation effect.

Again, while external influences certainly play a role, people's perceptions, attitudes, and intentions influences their ultimate behavior to use a technology. Extant research often proposes that intentions are the most proximal antecedent to be behaviors as people perform behaviors that they intend to perform unless external influences prevent such behaviors. We argue above that task-technology fit and misfit influence intentions via perceptions and attitudes and, therefore, believe them to ultimately influence behaviors via their prior effect on perceptions, attitudes, and intentions.

- H6:** A) Task-technology fit, b) too little, and c) too much each have indirect effects on use via perceived usefulness, perceived ease of use, attitude towards use, and behavioral intentions.

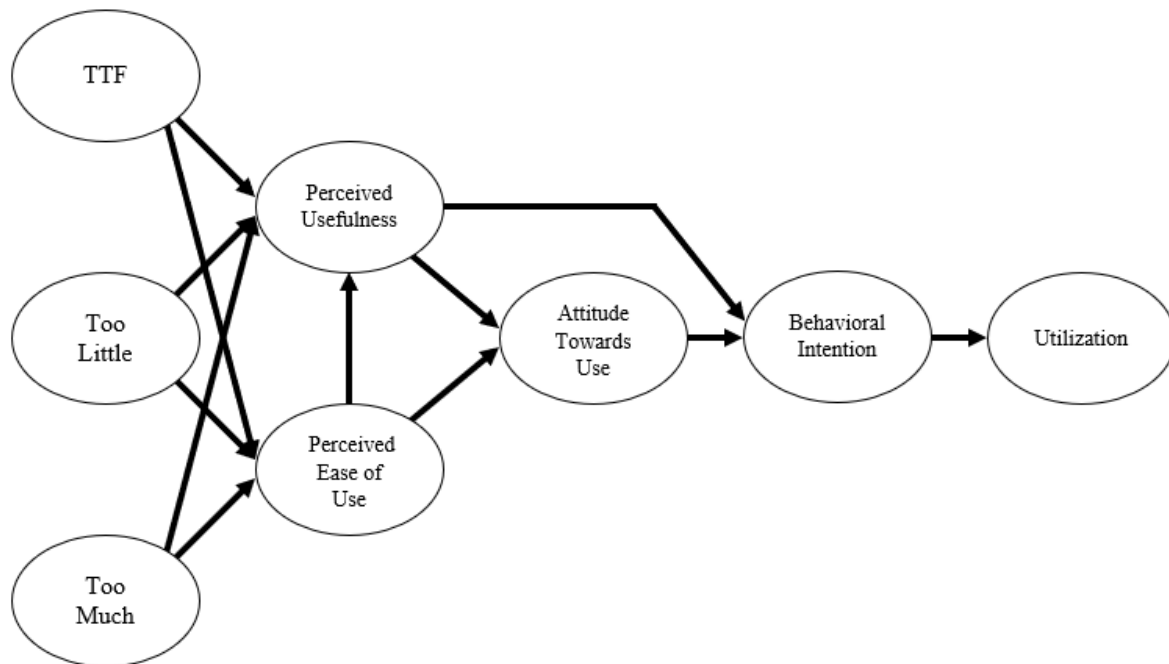


Figure 1. Proposed Theoretical Model

### 3 Methods

#### 3.1 Participants

We recruited participants ( $N = 642$ ,  $M_{age} = 36.66$ ,  $SD_{age} = 10.61$ , 43% female, 92% American) from MTurk and provided a modest amount of monetary compensation. When we conducted the study, all participants had employment (100%) and represented myriad industries (business and information (21%), education (13%), finance and insurance (13%), health services (9%), other (44%)) and years of experience ( $M_{tenure} = 6.81$ ,  $SD_{tenure} = 6.37$ ). MTurk is an online platform that connects individuals who want to perform tasks online, such as taking a survey, with those needing the tasks completed. Prior studies have shown that researchers can obtain reliable and valid results from MTurk samples if they take proper precautions (e.g., attention checks; Barends & de Vries, 2019; Buchheit et al., 2019; Hauser & Schwartz, 2016; Rouse, 2019). We removed participants from the analyses if they failed more than 20 percent of the attention checks (e.g., "Please mark agree to show that you are paying attention"). Thereby, participants that participated in four or five data-collection waves could, thereby, miss one attention check, whereas participants that participated in one, two, or three data-collection waves could not miss any. We also removed participants if they provided nonsensical answers to the questions regarding the technology that they used most at work and its associated task and/or answered regarding different technologies and tasks across the multiple surveys (see below). All statistics, including the reported sample sizes above and below, reflect the sample after we removed these participants.

#### 3.2 Procedure

Participants signed up for the study via MTurk. They provided their informed consent and completed the first survey ( $N = 642$ ), which included measures of ttf, too little, and too much. We administered each following surveys one week apart. The second survey ( $N = 293$ ) included measures of perceived ease of use and perceived usefulness. The third survey ( $N = 242$ ) included a measure of attitude towards use. The fourth survey ( $N = 194$ ) included a measure of behavioral intention to use. Lastly, the fifth survey ( $N = 181$ ) included a measure of use.



### 3.3 Measures

We measured all responses on a scale from strongly disagree (1) to strongly agree (7). Each survey began with specific instructions from Howard and Rose (2019). These instructions asked the participants to indicate which technology they used the most at work and the primary task that they completed using that technology. We then told them to answer all items regarding their written technology and task and that their written technology and task must be the same for each survey. As we note above, we removed participants that wrote different technologies and tasks across their surveys from all analyses. We provide all items in Appendix A.

#### 3.3.1 Task-technology Fit and Task-technology Misfit

We measured task-technology fit, too little, and too much with Howard and Rose's (2019) scale. We asked participants to respond to six items for task-technology fit, six items for too little, and six items for too much. Example items include "The technology matches the task" (task-technology fit), "The technology falls short that what is needed for the task" (too little), and "The technology is more than what is needed by the task" (too much). The dimensions produced appropriate Cronbach's alphas (task-technology fit  $\alpha = 0.91$ ; too little  $\alpha = 0.96$ ; too much  $\alpha = 0.95$ )

#### 3.3.2 Perceived Ease of Use

We measured perceived ease of use with six items that we adapted from Dumpit and Fernandez's (2017), Wu and Chen's (2017), and Manis and Choi's (2019) scales. An example item includes "Overall, the technology is easy to use". The scale's Cronbach's alpha was 0.94.

#### 3.3.3 Perceived Usefulness

We measured perceived usefulness with six items that we adapted from Dumpit et al.'s (2017) and Wu and Chen's (2017) scales. An example item includes "I believe that the technology improves my performance on the task". The scale's Cronbach's alpha was 0.91.

#### 3.3.4 Attitude Towards Use

We measured attitude towards use with eight items that we adapted from Wu and Chen's (2017) and Manis and Choi's (2019) scales. An example item includes "My impression of the technology is positive". The scale's Cronbach's alpha was 0.94.

#### 3.3.5 Behavioral Intention

We measured behavioral intention with five items that we adapted from Wu and Chen's (2017) and Manis and Choi's (2019) scales. An example item includes "I intend to use the technology within the foreseeable future". The scale's Cronbach's alpha was 0.90.

#### 3.3.6 Use

We measured use with seven self-created items and asked participants to respond regarding their behaviors in the past week. An example item includes "I used the technology often". The scale's Cronbach's alpha was 0.95.

## 4 Results

We present the composite correlations and average variance extracted (AVE) in Table 1, and we present Pearson correlations of averaged scale scores and Cronbach's alphas in Appendix B. We tested all hypotheses via PLS-SEM by using SmartPLS 3 and following prior authors' recommendations (Cepeda-Carrion et al., 2019; Hair et al., 2020; Hair et al., 2022; Hair et al., 2019; Khan et al., 2019; Ringle & Sarstedt, 2016; Sarstedt et al., 2019). We chose to apply PLS-SEM because, with it, we could assess our entire model simultaneously. As prior authors have noted (Chau, 1996; Lee et al., 2003; Marangunic & Granic, 2015; Rafique et al., 2020), the TAM proposes a sequential series of relationships that build on each other. For this reason, it would be inappropriate to assess the model's individual relationships in a piecemeal approach; rather, one should assess the model holistically. Similarly, we expect that task-technology fit and task-technology misfit may somewhat overlapping predictive abilities. Thus, one needs to simultaneously

assess both task-technology fit's and task-technology misfit's relationships together rather than assess their relationships independently.

**Table 1. Composite Correlations and Square Root of Average Variance Extracted**

	1	2	3	4	5	6	7	8
1) TTF	0.83							
2) Too little	-0.58**	0.92						
3) Too much	-0.20**	0.31**	0.85					
4) Perceived ease of use	0.27**	-0.31**	-0.07	0.88				
5) Perceived usefulness	0.45**	-0.35**	-0.05	0.41**	0.84			
6) Attitude towards use	0.50**	-0.43**	-0.04	0.52**	0.70**	0.83		
7) Behavioral intention	0.43**	-0.36**	-0.13	0.27**	0.50**	0.47**	0.87	
8) Use	0.33**	-0.23**	-0.10	0.32**	0.39**	0.38**	0.56**	0.89

Square root of average variance extracted (AVE) listed on diagonal.  
 \* p < 0.05  
 \*\* p < 0.01

Further, we chose to apply PLS-SEM rather than covariance-based SEM (CB-SEM) for many reasons. Our model included eight latent variables and five to eight items to represent each one, which constitutes a relatively complex structural model (Brown, 2015; Kline, 2015). The CB-SEM method often does not converge when estimating complex models, but PLS-SEM can perform quite well in these conditions (Hair et al., 2022). Moreover, PLS-SEM represents the preferred technique for examining mediated relationships that involve structural models (Sarstedt et al., 2020). In addition, our sample size is comparable to prior studies on E-TTF theory and the TAM (Howard & Rose, 2019; Scherer et al., 2019; Yousafzai et al., 2007a, 2007b), and we successfully met the sample size recommendations for PLS-SEM (Hair et al., 2022). Lastly, our study represents the first effort to integrate E-TTF theory with the TAM; thereby, one could consider our analyses more exploratory rather than confirmatory. Many prior authors have strongly recommended that one use PLS-SEM when conducting more exploratory analyses (although more researchers have also begun to also recommend the analysis for confirmatory approaches; Hair et al., 2020; Ringle & Sarstedt, 2016; Sarstedt et al., 2019). For these reasons, we were confident that PLS-SEM would provide accurate estimates for our model.

To evaluate our PLS-SEM results, we followed the confirmatory composite analysis (CCA) sequence that Hair et al. (2020) recommend. In the CCA sequence, one begins by assessing outer item loadings (i.e., measurement model), which indicate the strength of relationships between items and their associated composite factors. We calculated statistical significance estimates via a bootstrapping approach with 5,000 resamples. One item had an item loading below 0.70, the standard cutoff for outer loadings (Hair et al., 2020; Hair et al., 2022; Hair et al., 2019). Once we removed this item from the analyses, all remaining items demonstrated item loadings above 0.70 (see Appendix C). Each composite's Cronbach's alpha (> 0.70), composite reliability (> 0.70), rho\_A (> 0.70), and AVE (> 0.50) exceeded traditional guidelines (Ringle & Sarstedt, 2016; Sarstedt et al., 2019), which supports the scales' convergent validity. Lastly, each composite passed the F-L (Fornell-Larcker) criterion test, and the heterotrait-monotrait ratios of each composite pairing did not exceed the standard 0.85 cutoff (Ab Hamid et al., 2017; Henseler et al., 2015). These results support each scale's discriminant validity. Together, these initial analyses support our decision to use PLS-SEM to analyze our structural model.

Next, we assessed our inner model relationships (i.e., path coefficients), which indicate the strength of relationships between the latent composites (see Table 2). To interpret these effects, we used beta coefficients to identify the direction, f2 values to identify the magnitude, and p-values to identify the significance of these relationships. We considered f2 statistics around 0.02 small, 0.15 moderate, and 0.35 large (Cohen, 1988; Hair et al., 2022). We visually illustrate our observed effects in Appendix D. Task-technology fit had positive and significant relationships with perceived usefulness ( $\beta = 0.331$ ,  $p < 0.01$ ,  $f2 = 0.102$ ) and perceived ease of use ( $\beta = 0.139$ ,  $p < 0.01$ ,  $f2 = 0.014$ ), with the former being moderate and the

latter being small. These results support H1a and H1b. Too little had a negative, small, and significant relationship with perceived ease of use ( $\beta = -0.237$ ,  $p < 0.01$ ,  $f^2 = 0.039$ ), which supports H2b; however, it did not have a significant relationship with perceived usefulness ( $\beta = -0.092$ ,  $p > 0.05$ ,  $f^2 = 0.007$ ), which does not support H2a. Too much had a non-significant relationship with both perceived usefulness ( $\beta = 0.065$ ,  $p > 0.05$ ,  $f^2 = 0.006$ ) and perceived ease of use ( $\beta = 0.027$ ,  $p > 0.05$ ,  $f^2 = 0.001$ ), which does not support H3a and 3b.

**Table 1. PLS-SEM Path Coefficients**

Predictor	Outcome	Path coefficient	P-value	$f^2$
Task-technology fit	Perceived ease of use	0.139	<b>0.042</b>	0.014
Task-technology fit	Perceived usefulness	0.331	< 0.001	0.102
Too little	Perceived ease of use	-0.237	0.003	0.039
Too little	Perceived usefulness	-0.092	0.162	0.007
Too much	Perceived ease of use	0.027	0.711	0.001
Too much	Perceived usefulness	0.065	0.463	0.006
Perceived ease of use	Attitude towards use	0.279	<b>&lt; 0.001</b>	0.144
Perceived ease of use	Perceived usefulness	0.299	<b>&lt; 0.001</b>	0.114
Perceived usefulness	Attitude towards use	0.582	<b>&lt; 0.001</b>	0.626
Perceived usefulness	Behavioral intention	0.340	<b>0.010</b>	0.083
Attitude towards use	Behavioral intention	0.234	0.116	0.039
Behavioral intention	Use	0.559	<b>&lt; 0.001</b>	0.453

Note:  $p < 0.05$  listed in bold.

Further, we report the TAM's relationships (see Table 2). Perceived ease of use had positive, moderate, and significant relationship with perceived usefulness ( $\beta = 0.299$ ,  $p < 0.01$ ,  $f^2 = 0.114$ ) and attitude towards use ( $\beta = 0.279$ ,  $p < 0.01$ ,  $f^2 = 0.144$ ). Perceived usefulness had a positive, very large, and significant relationship with attitude towards use ( $\beta = 0.582$ ,  $p < 0.01$ ,  $f^2 = 0.626$ ). Attitude towards use had a non-significant relationship with behavioral intentions ( $\beta = 0.234$ ,  $p > 0.05$ ,  $f^2 = 0.039$ ), but perceived usefulness had a positive, moderate, and significant relationship with behavioral intentions ( $\beta = 0.340$ ,  $p < 0.01$ ,  $f^2 = 0.083$ ). Behavioral intentions had a positive, large, and significant relationship with use ( $\beta = 0.559$ ,  $p < 0.01$ ,  $f^2 = 0.453$ ). We found support for all TAM relationships except the link between attitude towards use and behavioral intentions.

We also assessed the total indirect effect that task-technology fit, too little, and too much had on the TAM variables (see Table 3) using the procedure that Sarstedt et al. (2020) outline. We only report these effects' direction and significance as no standard guidelines exist to interpret the magnitude of indirect effects using PLS-SEM in the current content domain. Task technology fit had positive and significant total indirect effects on attitude towards use ( $c = 0.256$ ,  $p < 0.01$ ), intention to use ( $c = 0.187$ ,  $p < 0.01$ ), and use ( $c = 0.104$ ,  $p < 0.05$ ). These results support H4a, H5a, and H6a. Too little had negative and significant total indirect effects on attitude towards use ( $c = -0.161$ ,  $p < 0.05$ ), intention to use ( $c = -0.093$ ,  $p < 0.05$ ), and use ( $c = -0.052$ ,  $p < 0.05$ ). These results support H4b, 5b, and 6b. Too much had non-significant total indirect effects on attitude towards use ( $c = 0.051$ ,  $p > 0.05$ ), intention to use ( $c = 0.037$ ,  $p > 0.05$ ), and use ( $c = 0.021$ ,  $p > 0.05$ ). These results fail to support H4c, H5c, and H6c. Together, these results indicate that the E-TTF theory's elements indeed predict the TAM's elements with both task-technology fit and too little producing significant direct and indirect effects on almost all such elements.

Table 4 provides statistics regarding the impact that the predictors had on the outcomes. R2 represents the model's in-sample predictive power regarding the specified outcome, whereas Q2 represents the model's out-of-sample predicted power regarding the specified outcome. According to the R2 values, the model predicted attitude towards use very well. It predicted perceived usefulness, behavioral intention, and use quite well and predicted perceived ease of use to a lesser extent. On the other hand, the Q2 values all exceeded zero, which indicates that the model had predictive relevance for each outcome. Therefore, these results jointly suggest that the model meaningfully predicted each TAM components, and Figure 2 visually represents our supported findings.

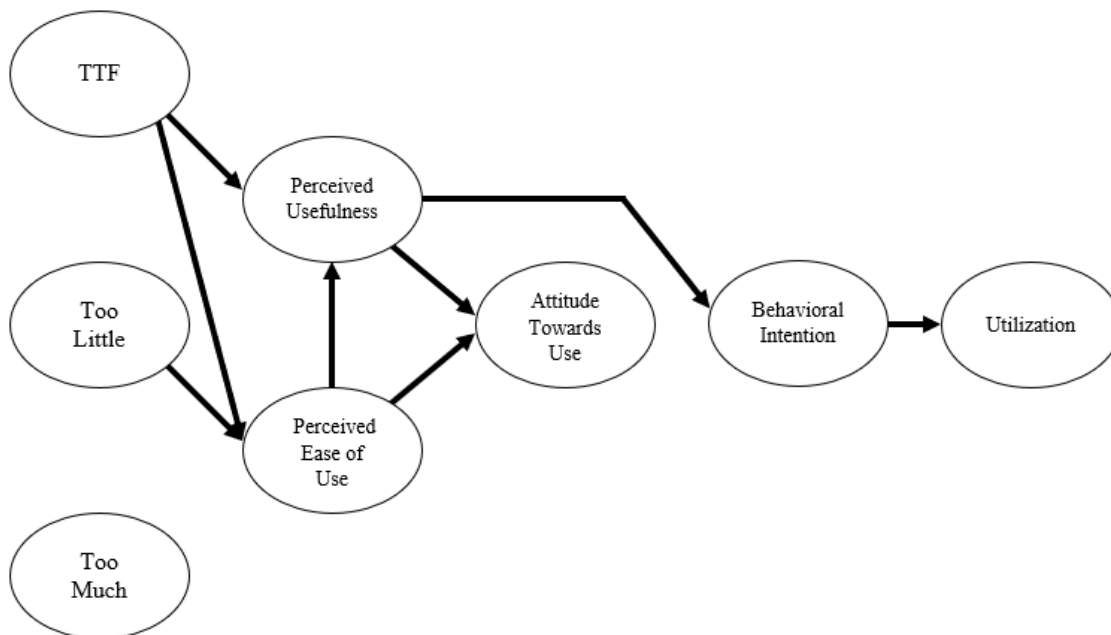
**Table 3. PLS-SEM Total Indirect Effects**

Predictor	Outcome	Total indirect effect	P-value
Task-technology fit	Attitude towards use	0.256	<b>&lt; 0.001</b>
Task-technology fit	Behavioral intention	0.187	<b>0.001</b>
Task-technology fit	Use	0.104	<b>0.012</b>
Too little	Attitude towards use	-0.161	<b>0.014</b>
Too little	Behavioral intention	-0.093	<b>0.017</b>
Too little	Use	-0.052	<b>0.031</b>
Too much	Attitude towards use	0.051	0.428
Too much	Behavioral intention	0.037	0.419
Too much	Use	0.021	0.438
Perceived ease of use	Behavioral intention	0.208	<b>&lt; 0.001</b>
Perceived ease of use	Use	0.116	<b>0.002</b>
Perceived usefulness	Behavioral Intention	0.136	0.111
Perceived usefulness	Use	0.266	<b>&lt; 0.001</b>
Attitude towards use	Use	0.131	0.148

p < 0.05 listed in bold.

**Table 4. PLS-SEM R<sup>2</sup> and Q<sup>2</sup> Values**

Outcome	R <sup>2</sup>	Q <sup>2</sup>
Perceived ease of use	0.108	0.116
Perceived usefulness	0.300	0.280
Attitude towards use	0.550	0.243
Behavioral intention	0.281	0.156
Use	0.312	0.035



**Figure 2. Supported PLS-SEM Model**

## 5 Discussion

In this paper, we integrate E-TTF theory with the TAM, an eminent theoretical perspective of technological adoption. In doing so, we further research and practice by extending our understanding of task-technology fit and task-technology misfit and by improving our predictive ability regarding use and associated constructs. Thus, our study could provide widescale theoretical implications.

We found that task-technology fit significantly predicted the initial two variables in the TAM, perceived ease of use and perceived usefulness. Task-technology fit also had significant indirect effects on all other variables in the TAM: attitude towards use, behavioral intention, and use. While too little did not have a significant relationship with perceived usefulness, it did have a significant relationship with perceived ease of use. It also had significant indirect effects on every other variable in the TAM. These findings suggest that one should see task-technology fit and too little as crucial to understanding how user perceptions develop and their subsequent use behaviors. The results also emphasize the need to study task-technology misfit in addition to task-technology fit. Including too little significantly improved our model because we found that task-technology fit did not capture its predictive variance was shown to not be captured with task-technology fit. Indeed, too little significantly predicted outcomes above and beyond task-technology fit, which means our model predicted a greater amount of variance in outcomes compared to a model that included task-technology fit alone. Therefore, we should see too little as essential to further investigations that involve task-technology fit.

Furthermore, too much did not predict any variables in the TAM (whether directly or indirectly). This finding further emphasizes the importance of Howard and Rose's (2019) multidimensional perspective of task-technology misfit. Studying task-technology misfit as a unidimensional construct would group the variance in too much and too little together, and too much's predictive ability (or lack thereof) would join too little's predictive ability. If so, too little would possibly no longer predict the variables in the TAM. Fortunately, this multidimensional perspective separates too much from too little, which separates each one's predictive ability and allows too little to effectively predict outcomes. Thus, while too much did not significantly predict any variable in the TAM, the non-significant results still demonstrate the importance need to integrate E-TTF theory in its entirety with the TAM.

We replicated most TAM relationships, which again supports its overall validity; however, we did not find support for one relationship: the one between attitude towards use and behavioral intentions. Previous research has also sometimes failed to find support for this relationship (Scherer et al., 2019; Yousafzai et al., 2007a, 2007b). As a result, researchers have removed it from some TAM iterations (Venkatesh & Davis, 2000), though they have reinserted it in the most recent ones (Abdullah & Ward, 2016; Scherer et al., 2019). Because the original and most recent TAM versions include this relation, we tested it in our model to allow our results to speak towards early and modern TAM research. Thus, while we did not expect to fail to support this relation per se, we also do not find this non-significant finding surprising.

### 5.1 Theoretical Implications and Future Research Directions

We discuss certain notable theoretical implications and future research directions in light of our findings. First, our results provide further support for E-TTF theory's validity. While Howard and Rose (2019) found robust support across multiple studies in their original investigation, researchers should always empirically replicate and reinvestigate theoretical frameworks. By demonstrating that their measures produced appropriate validity information and similar interrelationships as their original investigation, we provide further support that researchers should continue to apply E-TTF theory. Future research should continue investigating instances in which too little predicts beyond task-technology fit as we did in our study. Too little may provide additional predictive ability regarding most outcomes already linked to task-technology fit; thus, researchers need to reinvestigate all prior studies on TTF theory through the lens of E-TTF theory. Doing so would further bolster task-technology misfit's theoretical and practical importance but also more deeply explain the interface between tasks and technologies.

Second, several authors have proposed too little and too much to have many possible outcomes (Howard & Gutworth, 2020; Hsiao, 2019; Li et al., 2019; Osang, 2019) but not yet tested these outcomes. We not only test task-technology misfit's novel outcomes but also broaden E-TTF theory's theoretical scope by linking too little and too much to the TAM. That is, one can now argue all constructs previously linked to the TAM elements in prior research to be also linked to task-technology misfit. These links may be indirect effects via the TAM's elements, but future research should also assess whether too little and too much have direct effects with these other variables. For instance, research has repeatedly linked the TAM to user

performance (Bagozzi et al., 1992; Davis et al., 1989; Lee et al., 2003; Marangunić & Granić, 2015; Rafique et al., 2020). Task-technology misfit could possibly relate to user performance via the mediating effects of the TAM's variables or it could have a direct effect on user performance independent of the TAM's elements. Further still, the TAM's relationship with these other outcomes could disappear when accounting for task-technology misfit due to the former's possibly stronger effects. Therefore, future research should continue to focus on integrating E-TTF theory and the TAM in assessing these novel outcomes as one framework may explain the other's or reduce its effects.

Third, too much did not emerge as a significant predictor in our study, and researchers have yet to link it to any other outcomes. While we theoretically and empirically need to distinguish too much from too little, future research should strive to find instances in which too much predicts outcomes as we mention above. It seems possible if not likely that present studies simply have yet to study outcomes or contexts in which too much is predictive. Thus, while current studies on E-TTF theory have proven informative, we clearly have much to discover.

Fourth, like many prior studies, we once again found support for the TAM's validity. The model still details whether users will adopt technologies quite well even decades after its creation (Bagozzi et al., 1992; Davis, 1985; Davis et al., 1989; King & He, 2006). Researchers continue to make new discoveries, and some have made recent revisions to the theoretical model (Abdullah & Ward, 2016; Scherer et al., 2019; Venkatesh, 2000; Venkatesh & Davis, 2000; Venkatesh et al., 2003). For instance, the TAM-3 identifies a host of antecedent effects to perceived ease of use and perceived usefulness but its core elements remain the same as in the original model. In this paper, we provide support to also link E-TTF theory to these recent revisions to the TAM, and we call for future researchers to investigate such integrations. Researchers could even begin a chronological approach to studying whether E-TTF theory integrates well with TAM revisions. That is, they could first integrate E-TTF theory with the TAM-2 (Venkatesh & Davis, 2000), then with the TAM-3 (Venkatesh & Bala, 2008), and then with the revised UTAUT (Dwivedi et al., 2019), and so on (Abdullah & Ward, 2016; Scherer et al., 2019; Venkatesh, 2000; Venkatesh et al., 2003). Each analysis could provide initial support for the following integration, and subsequent studies could build on robust prior findings. Therefore, our effort here represents the first among many potential investigations into integrating E-TTF theory and the TAM.

Fifth, the E-TTF theory predicted the TAM variables quite well, but we could have also included other antecedent effects. For instance, Venkatesh and Davis (2000) identified five possible antecedents to perceived usefulness, and Venkatesh and Bala (2008) identified six additional possible antecedents to perceived ease of use. Researchers should incorporate these findings in further integrations to determine the extent to which E-TTF theory predicts variables in the TAM when accounting for other influences. Task-technology fit and task-technology misfit may even serve as mediators between these previously discovered antecedents and perceived ease of use as well as perceived usefulness. That is, these previously identified antecedents may not influence perceived ease of use and perceived usefulness directly but instead may influence task-technology fit and task-technology misfit, which subsequently influence the TAM constructs. If true, then E-TTF theory may be essential to understanding contemporary TAM extensions.

Sixth, in this paper, we argue that one needs to use statistical approaches that can simultaneously analyze entire models when studying the TAM, and we applied contemporary best practices for one such analysis: PLS-SEM. Future researchers should mimic our approach in applying this analysis and no longer assess the TAM in a piecemeal manner. Doing so would provide deeper theoretical inferences about whether users will adopt technologies by applying sophisticated statistical analyses. Thus, with this paper, we provide both important theoretical implications but also notable methodological implications.

## 5.2 Practical Implications

Many organizations benefit from understanding why employees adopt new technologies, which has led to the TAM's widespread application. Our results benefit practice by showing that task-technology fit, too little, and too much can explain significant variance in use and other associated antecedents. Organizations should investigate new user-adoption routes via the lens of the E-TTF theory. For instance, many authors have reported that employees resist using new technologies intended to streamline organizational processes—often because they find them unfamiliar and difficult to use (Lee et al., 2003; Marangunić & Granić, 2015; Rafique et al., 2020). Organizations should ensure that they maximize the task-technology fit of their applied technologies but also that the employees can understand this fit. That is, organizations may need to provide supplemental information regarding the manner in which the technology matches the task. By doing so, employees may more readily adopt the technologies, which could help streamline processes.

Organizations also benefit from using our E-TTF theory and TAM integration to understand why customers adopt new technologies. For instance, our integration could help both business-to-customer organizations (e.g., software companies would benefit from understanding why customers may use their software rather than a competitor's software (and vice versa)) and business-to-business organizations (e.g., software companies would benefit from understanding why employees may be reluctant to use their software rather than a prior software). When developing their technologies, organizations can use their results as a lens to understand user adoption both inside and outside their walls.

Furthermore, researchers have frequently applied task-technology fit to understand why certain technologies may work particularly well (or poorly) in specific contexts. By finding support for E-TTF theory, we further emphasize how task-technology misfit can provide added benefits in understanding these technologies and their applied contexts. Practitioners should not ignore misfit's dynamics when applying technologies; otherwise, employees may face reduced performance outcomes. High task-technology fit may possibly cause users to thrive at their activities but low task-technology fit may not differentiate poor performers and average performers. Instead, practitioners must understand task-technology misfit's dynamics to differentiate these two user categories.

Lastly, organizations can also benefit from the knowledge that too little influences the two outcomes behavioral intention and use whereas too much does not. In designing future technologies, organizations may need to be more mindful of not including enough features rather than including too many. Users may be able to work through the difficulties of having access to too many features, eventually perform their tasks well, and, ultimately, continue to use a technology. On the other hand, users seem to quickly notice when technologies do not include certain features and they will likely immediately stop using such technologies in such situations. Thus, developers should likely place a greater focus on too little more so than too much.

### 5.3 Limitations

As with all papers, this one has some limitations. We applied a time-separated design and measured variables separately or together as prior research has typically done (Chau, 1996; Lee et al., 2003; Marangunić & Granić, 2015; Rafique et al., 2020). For instance, we measured task-technology fit, too little, and too much together at the same timepoint; we measured perceived ease of use and perceived usefulness together at a different timepoint; and we measured attitude towards use, behavioral intentions, and use each at separate timepoints. In doing so, we could temporally separate most of our tests of indirect effects, and we can claim that the antecedent preceded the outcome for most observed direct effects. Because we measured perceived ease of use and perceived usefulness at the same timepoint, however, we cannot be as certain regarding the causality direction in this relationship. For this reason, future researchers should continue studying the TAM using sophisticated designs with additional timepoints to disentangle the relationship between these two variables.

Also, we used self-reported data for all variables in the current study. Although we applied techniques to reduce common-method bias, such as our time-separated research design, future researchers should reanalyze the current model using different measurement approaches. For instance, some authors have proposed that one can measure task-technology fit in many different manners, perhaps even as a group-level construct (Cane & McCarthy, 2009; Venkatraman, 1989). Aggregating task-technology fit and task-technology misfit to the group level could identify novel dynamics regarding the constructs; therefore, future researchers could more deeply understand E-TTF theory using such research designs.

Lastly, we obtained our sample via MTurk. Some studies have expressed concern about using MTurk samples when one does not take sufficient precautions, but we took such precautions in this case (Barends & de Vries, 2019; Buchheit et al., 2019; Hauser & Schwartz, 2016; Rouse, 2019). In particular, we applied multiple attention checks, and our study design included many timepoints. We believe that we included only sufficiently motivated participants in our study, but, as with all research, future authors should replicate our results using alternative research designs.

## 6 Conclusion

In this paper, we integrate E-TTF theory with the TAM. We found that that task-technology fit predicted the initial two variables in the TAM (perceived ease of use and perceived usefulness), too little predicted perceived ease of use, and too much predicted neither. Through these initial linkages, we found that task-technology fit and too little subsequently had an indirect effect on the remaining TAM constructs, which demonstrates that E-TTF theory has large implications for the applying and understanding the TAM. From

these findings, we envision future research repeatedly applying this integration to better understand why users adopt new technologies—and making new discoveries of their own from these studies.



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## Appendix A

### Items Administered in the Current Paper

**The first survey began with the following two items.**

- 1) At work, employees are often expected to use many different technologies. Think about the technology that you use the most at work. If you are thinking about a technology that can run many different programs, such as a computer, think about a specific program on that technology. Please write the technology that you are thinking about in the space below. Some examples are: mobile commerce platform, internal information system, mechanical press, compact excavator, wheel forwarder, IBM SPSS, Adobe Dreamweaver, and Microsoft Outlook.

**Also, please write a technology that you will remember! You will be asked about this technology on all follow-up surveys!**

- 2) Now, think about the task that you use this technology for most often. Write two to four words describing this task in the space below.

**All following surveys began with the following two items.**

- 1) Last week, you were asked to list the technology that you use the most at work. Please write that technology again in the box below.
- 2) Last week, you were asked to list the task that you use this technology for most often. Please write that task again in the box below.

**All scales included the following instructions (in addition to any scale-specific instructions):**

Please indicate the extent that you disagree to agree with the following statements in regards to the technology and task that you wrote in the space above.

In the items below, “the technology” refers to the technology that you wrote above, and “the task” refers to the task that you wrote above.

#### **Task-technology fit**

- 1) The technology matches the task.
- 2) The technology suits the task.
- 3) The technology corresponds well to the task.
- 4) The technology fits the task.
- 5) The technology is in sync with the task.
- 6) The technology has the exact functions needed for the task.

#### **Too little**

- 1) The technology falls short of what is needed for the task.
- 2) The technology lacks certain features to do the task.
- 3) The technology is less than what is needed by the task.
- 4) The technology has less-than-enough features to complete the task.
- 5) The technology is lacking in features to perform the task.
- 6) The technology has fewer features than needed for the task.

**Too much**

- 1) The technology has too much to perform the task.
- 2) The technology is larger than needed to do the task.
- 3) The technology is more than what is needed by the task.
- 4) The technology contains more than what is needed for the task.
- 5) The technology seems greater than the task.
- 6) The technology provides much more than is needed to perform the task.

**Perceived usefulness**

- 1) I believe that the technology improves my performance on the task.
- 2) Using the technology enhances my effectiveness on the task.
- 3) Using the technology makes the task easy.
- 4) Using the technology improves my ability to perform the task.
- 5) Using the technology makes me more productive at the task.
- 6) Overall, the technology is useful to me in performing the task.

**Perceived ease of use**

- 1) Learning to use the technology is easy.
- 2) It is easy to become proficient in using the technology.
- 3) The interaction with the technology is clear and understandable.
- 4) Using the technology is clear and understandable.
- 5) I had an easy time learning how to use the technology.
- 6) Overall, the technology is easy to use.

**Attitude towards use**

- 1) I believe that using the technology is a good idea.
- 2) I believe that using the technology is advisable.
- 3) I am satisfied in using the technology.
- 4) My impression of the technology is good.
- 5) My impression of the technology is positive.
- 6) My impression of the technology is satisfactory.
- 7) My impression of the technology is favorable.
- 8) My impression of the technology is pleasant.

**Behavioral intention**

- 1) I intend to continue to use the technology in the future.
- 2) I will continue using the technology increasingly in the future.
- 3) My intentions are to continue using the technology in the future, at least as active as today.
- 4) There is a high likelihood that I will use the technology within the foreseeable future.
- 5) I intend to use the technology within the foreseeable future.
- 6) I will use the technology within the foreseeable future.
- 7) Using the technology in the foreseeable future is important to me.

**Use (in past week)**

- 1) I used the technology often.
- 2) I used the technology quite a bit.
- 3) I frequently used the technology.
- 4) There were many occasions that I used the technology.
- 5) I often used the technology to perform the task.
- 6) There were many times that I used the technology to perform the task.
- 7) I regularly used the technology to perform the task.



## Appendix B

**Table B1. Pearson Correlations of Average Scale Scores and Cronbach's Alphas**

	1	2	3	4	5	6	7	8
1) TTF	0.91							
2) Too little	-0.58**	0.96						
3) Too much	-0.17**	0.28**	0.95					
4) Perceived ease of use	0.32**	-0.35**	-0.07	0.94				
5) Perceived usefulness	0.54**	-0.40**	-0.02	0.41**	0.91			
6) Attitude towards use	0.58**	-0.49**	-0.01	0.50**	0.70**	0.94		
7) Behavioral intention	0.52**	-0.38**	-0.09	0.29**	0.53**	0.55**	0.90	
8) Use	0.42**	-0.27**	-0.08	0.32**	0.40**	0.42**	0.58**	0.95

We list Cronbach's alphas listed on diagonal.  
 \* p < 0.05  
 \*\* p < 0.01

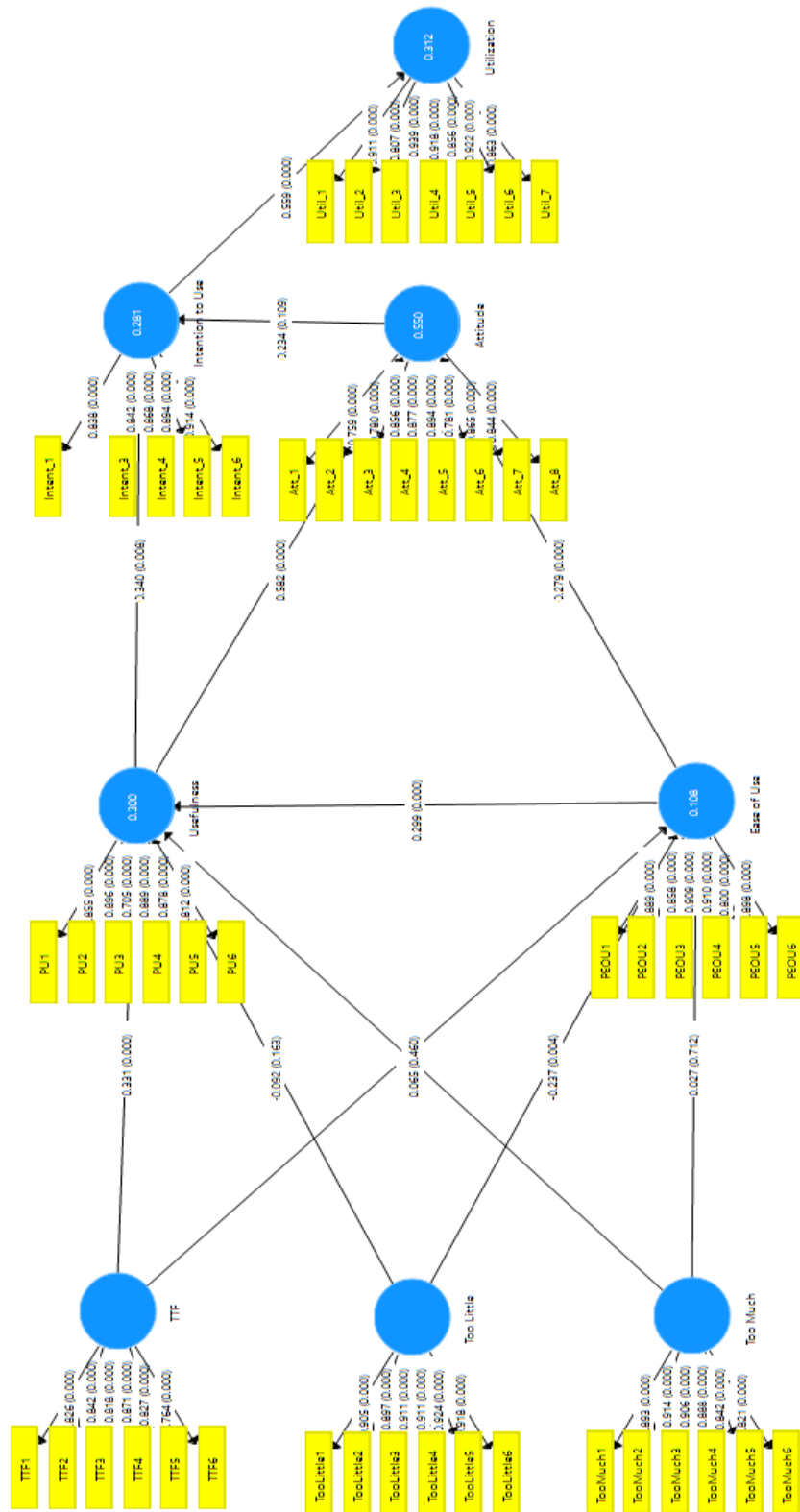
## Appendix C

**Table C1. PLS-SEM Outer Model Loadings**

Item	Loading	Item	Loading
TTF 1	0.826	Perceived Usefulness 1	0.855
TTF 2	0.842	Perceived Usefulness 2	0.896
TTF 3	0.818	Perceived Usefulness 3	0.705
TTF 4	0.871	Perceived Usefulness 4	0.889
TTF 5	0.827	Perceived Usefulness 5	0.878
TTF 6	0.764	Perceived Usefulness 6	0.812
Too little 1	0.905	Attitude Towards Use 1	0.759
Too little 2	0.897	Attitude Towards Use 2	0.780
Too little 3	0.911	Attitude Towards Use 3	0.856
Too little 4	0.911	Attitude Towards Use 4	0.877
Too little 5	0.924	Attitude Towards Use 5	0.894
Too little 6	0.918	Attitude Towards Use 6	0.781
Too much 1	0.893	Attitude Towards Use 7	0.865
Too much 2	0.914	Attitude Towards Use 8	0.844
Too much 3	0.906	Behavioral Intention 1	0.838
Too much 4	0.888	Behavioral Intention 2	0.842
Too much 5	0.842	Behavioral Intention 3	0.868
Too much 6	0.821	Behavioral Intention 4	0.894
Perceived ease of use 1	0.889	Behavioral Intention 5	0.814
Perceived ease of use 2	0.858	Use 1	0.911
Perceived ease of use 3	0.909	Use 2	0.807
Perceived ease of use 4	0.910	Use 3	0.939
Perceived ease of use 5	0.800	Use 4	0.918
Perceived ease of use 6	0.898	Use 5	0.856
		Use 6	0.922
		Use 7	0.863

In an initial model, one behavioral intention item produced a loading below 0.700, so we removed it and reanalyzed the model. The outer model loadings above represent the final model with this one item removed.

## Appendix D



**Figure D1. Visual Illustration of PLS-SEM Structural Model Results<sup>1</sup>**

<sup>1</sup> Outer model values represent item loadings and p-values. Inner model values represent path coefficients and p-values.

## About the Authors

**Matt C. Howard** is an associate professor in the Mitchell College of Business at the University of South Alabama. He received his PhD in Industrial/Organizational Psychology from the Pennsylvania State University. His research interests include statistics and methodologies, health and well-being, personality and individual differences, as well as technology-enhanced training and development. He has published lead-authored works in the *Journal of Applied Psychology*, *Organizational Research Methods*, *Journal of Organizational Behavior*, *Journal of Business Research*, *Information & Management*, *Human-Computer Interaction*, *Computers in Human Behavior*, *Computers & Education*, and now the *AIS Transactions on Human-Computer Interaction*. He currently serves on the editorial boards of the *Human Resource Management Journal*, *Human Resource Management*, and *Journal of Business and Psychology*. More information about the author can be found at [MattCHoward.com](http://MattCHoward.com).

**Joseph F. Hair Jr.** is the Director of the PhD Program in Business Administration, Mitchell College of Business, University of South Alabama, U.S.A. He ranks #1 globally in Marketing, Multivariate Data Analysis, SEM and PLS-SEM. His career citations exceed 340,000 and his h-index and i-10 index are 109 and 463, respectively. He has published over 85 editions of his books, including *Multivariate Data Analysis*, *Essentials of Business Research Methods*, Routledge, *A Primer on Partial Least Squares Structural Equation Modeling*, *A Primer on Partial Least Squares Structural Equation Modeling: R Version*, and *Essentials of Marketing Analytics*. He has published 160+ articles in scholarly journals such as the *Journal of Marketing Research*, *Journal of Academy of Marketing Science*, *Organizational Research Methods*, *Harvard Business Review*, *European Journal of Marketing*, *Journal of Family Business Strategy*, *European Management Journal*, and others.

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